Responding to the Forecast: Towards the Integration of Machine State Prediction and Required Maintenance Services

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Abstract: Machines become increasingly complex. At the same time, more and more sensors are installed and information is gathered in order to enable a close to real-time prediction of a machine's state. Companies try to implement Predictive Maintenance strategies to avoid machine downtimes on a large scale. For this purpose, artificial neural networks are applied more and more often. However, the classification of machine states with artificial neural networks is still not accurate enough. This is partially due to a lack of standards in data processing and in the harmonization of data from different sensor types. We aim to contribute to close these research gaps by developing a standard PM concept for machine and plant manufactures.

Keywords: Predictive Maintenance, Big Data Analytics, Sensor Data Processing, Neural Networks, Automated Diagnostics, Decision Support Systems.

1 Introduction

Machinery is a substantial resource to most industrial manufacturing processes. Especially IT-based manufacturing strategies heavily rely on the proper functioning of the involved machines [Pe07]. Thus, a functional fault - in worst case scenarios a total failure - implies serious problems and causes costs to companies of all sizes and industries. Therefore, the provision of after-sale-services (e.g. maintenance and repair) is a core element of hybrid value creation business models in the engineered products industry [Ro07]. The goal of such services is the preservation and recovery of operations, whilst providing high quality in terms of time, cost and execution. Furthermore, the provision of maintenance services is a means to create new business opportunities and increase overall revenue.

In recent years the amount and the variety of sensory technology implemented in machines has increased considerably. At the same time, a bundle of new production concepts, amongst others the idea of smart factories and close machine-to-machine-communication, have been outlined [La14]. Based on a high degree of sensor and actua-

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tor integration, industrial machines should be able to recognize what they produce and provide individual product configurations. However, this newly available sensory information is also suitable for machine error diagnosis and the establishment of Predictive Maintenance (PM) strategies, i.e. proactive maintenance service scheduling in order to avoid machine downtimes. Consequently, IT departments and engineers today have to deal with vast amounts of data, trying to produce structured error information and identifying a distinct cause of malfunctioning by data analysis. One approach, which seems particularly promising in the field of automated sensor data processing for machine and part condition classification is the application of Artificial Neural Networks (ANN). However, some challenges remain to be resolved in order for such a process to reach market maturity. We address the topic of PM from an Information Systems' perspective and outline a concept for the integration of machine diagnostics and maintenance services based on ANN.

The remainder of the paper is structured as follows: In section two, the research gap on ANN-based PM strategies and our research design are described. Following a brief introduction to automated sensor data processing with artificial neural networks, section three provides a summary of ANN applications in PM scenarios. In section four, we describe our current state of research and a use case of an ANN-based PM strategy in a German machine building company. Section 5 concludes with our main findings and provides an outlook on our forthcoming research.

2 Research Gap and Research Design

The practical need for PM concepts is not new. Engineering sciences address this topic since the late 1950s in order to achieve optimized maintenance service cycles. [IV88] provide an early work on PM strategies in the field of Information Systems. Although PM seems to become a more and more effective concept in the improvement of service efficiency and service quality, until today only few actually implemented PM concepts are known. Especially small and medium-sized businesses consider PM still a rather complex mathematical construct. The perceived complexity of PM strategies is fuelled even further by the increased information variety and density from sensor data. Highly individual and sophisticated diagnostic and early warning systems are almost exclusively developed in large enterprises with own departments for research and development [FAU15].

In the context of PM, ANN gain more and more importance. Compared to commonly used statistical forecasting approaches, ANN provide a set of highly dynamic, adaptive and flexible algorithms and procedures. They might even be able to learn and improve themselves from such circumstances. Overall, the application of ANN requires rather few assumptions and data characteristics. They enable, for instance, to process even unsteadily gathered data from different sensor types at the same time and provide robust and highly accurate predictions of condition developments.

However, a major problem and thus a central research gap in automated machine diagnostics is the accuracy of error identification being still too low [HB11], [HT13]. This means, an ANN-diagnostic system might identify an imminent failure, while the machine actually works just fine. This leads to costs due to unnecessary maintenance work and an unnecessary exchange of machine parts. Such false detections can have many causes. For example, faulty data processing during the harmonization of signals of different sensor types could lead to distortions. Furthermore, it is possible that multicollinearity, due to "wanted redundancy" of data, causes estimation errors. Wanted redundancy can arise, for example, by analysing the data of multiple temperature sensors that are located at different positions of a machine. The sensors might show the same values at all times, which causes the data to be fully correlated, but actually they do not provide the same information. Hence, such sensor information should not be removed in data pre-processing.

Another research gap is the often missing link between the understanding of a machine's state and the identification of the appropriate reaction to this state. Besides the analytic and diagnostic components in/on a machine, also the appropriate usage of the gained information needs to be addressed. In order to establish an effective PM strategy, it is not enough to detect failures or the need for maintenance. It is necessary to identify the actually needed service and to provide an IT-infrastructure to directly trigger or schedule this service. Consequently, the current research on PM is highly related to Decision Support Systems, Recommender Systems and the modular service design. In order to develop a robust taxonomy of machine or part conditions and a required maintenance service, which is as comprehensive as possible, findings from these fields of study need to be utilized.

To close the outlined research gaps, we follow an approach based on Design Science Research. In line with the research model of [SvB12], we will divide the individual research gaps into concrete and practical questions and develop prototypes to solve the resulting problems. This applies to possible architectures, data cores and ultimately entire smart recommender systems. The practical application and use of the prototypes and their evaluation is also part of our research agenda.

3 Related Works

3.1 A Brief Introduction to Neural Networks

The first ANNs have been developed in the 1940s. Already in 1943 McCulloch and Pitts describe the concept of solving analytical problems by means of networks of neurons [MP43]. Based on this work, [Ro58] introduced a layer architecture for such networks. This architecture today is referred to as the first Multi-Layer Perceptron (MLP), a network of neurons that can be trained to solve complex nonlinear problems. After a short period of stagnation, [Ko82] presented a new type of neural network that is trained and conditioned based on so-called self-organizing feature maps (SOM). These SOM networks were the first self-learning networks. They can be used without the initial need for historical data. When [RHW86] presented backpropagation, a learning and training concept, which enabled to model self-improving and recurrent interrelationship detection, the research on ANN ultimately became revitalised again. An ANN enables to transform multidimensional input-information into a certain number of unambiguous output classes and consists of three different areas: An input layer, an output layer and n hidden layers.

Field of Application	Common Inputs	Common Outputs	Advantages	Drawbacks
Supervised training: FFNN				
Sensor data classification without considering external stimuli	Numerical sensor data a usually one category of sensors	Identification of 1 machine state out of a predefined set of allowed states	Low complexity; Fast training; Low computational costs	No identification of new output classes; No instant analysis
Supervised training: RNN				
Sensor data classification in presence of external stimuli	Numerical sensor data	Identification of 1 machine state out of a predefined set of allowed states	Highly flexible interrelationship modelling; Quick response to external stimuli	No identification of new output classes; No instant analysis
Unsupervised training: SOM / ART				
Pattern recognition and determination of different output classes	Digital images, numerical sensor data, mixed sensor information and data formats	Individual, free classification and forecasting with endogenously identified outputs and output classes	Self-learning algorithms	Highly complex; unknown accuracy

Tab. 1: Different types of neural networks and their properties

The actual computing and information processing is carried out in the hidden layers, whereas the number of hidden layers not necessarily is restricted. The hidden layers usually contain an unspecified number of neurons in order to model the impact and interdependencies of all input variables. Thereby an ANN is able to model even complex nonlinear relationships, which is one of the most striking advantages of ANN compared to widely used statistical procedures, for a comparison see [Zo07]. To be used for classification purposes, an ANN needs to be trained. The kind of training – supervised or unsupervised – and the restrictions on the considered directions of relationships across the individual layers determine the type of an ANN. The training of an ANN is called supervised when the training is carried out whilst the possible output classes and actual outputs are known in advance. In this case, the training procedures are repeated until the cumulated error, i.e. the cumulated difference between the estimated and the actual output values, is below a predefined threshold level. If no backward feedback between the layers is accepted and all layers are processed in sequence during the training, the ANN is referred to as feedforward neural network (FFNN). If bidirectional feedback is possible, a recurrent neural network (RNN) is computed. If no dataset with known results is available for training, unsupervised – self-learning – networks need to be applied. The most important ANNs based on unsupervised learning algorithms are self-organizing feature maps (SOM) and adaptive resonance theory networks (ART), which have been introduced by [Gr76] and [CG87].

The scientific literature on ANN-based PM strategies mostly describes applications of FFNN and RNN. For condition monitoring and diagnostics, this has advantages and disadvantages at the same time. On the one hand, already analysed historical data, including already identified defects and failures needs to be available for network conditioning. This leads to a predefined output cluster structure and enables only to detect already known machine or part conditions in new data. On the other hand, since the networks are conditioned with respect to an acceptable error threshold value, it is possible to measure the accuracy of the ANN. Although the training is faster for a FFNN than for the RNN, due to its abilities to handle more complex environments and to adapt to external stimuli, the latter appears to be preferred in literature. A comparison of FFNN and RNN can be found at [Br12].

Unsupervised trained networks can be applied to problems, where no or rather little information on the actual structure of the outcome of an analysis are known in advance. SOM and ART algorithms endogenously identify the different types of outputs. Hence, they are rather employed to solve clustering problems. For an outline on SOM see [RMD02]. Although this might seem as an advantage in error or failure detection, such approaches can hardly be applied in standardized PM strategies. Since an error or failure that is detected by such an ANN is likely to be unknown to the maintenance management, there is no required service linked to it, yet. Consequently, SOM and ART networks are rather to be used in the definition of a PM system than in the decision support system (DSS) itself.

3.2 Neural Networks in Predictive Maintenance Strategies

For forecasting and data classification purposes, ANN are applied across all industries. Particularly in the engineered products and power supply industries, several approaches have been outlined and application studies have been published. [ALU93] describe a procedure for the condition monitoring of ball bearings based on vibration analysis with a simple RNN. By analysing data from acoustic sensors, which measured the vibration of the bearings in operation, their network classified the bearing into 1 of 6 predefined conditions. [Ma97] developed a similar approach to monitor the deterioration of Carbon Fibre Reinforced Plastic (CFRP) surfaces, analysing data from temperature sensors with a Bayesian network. Thermal information has also been used in multiple ANN-based condition monitoring approaches on electronic equipment. For instance, [Al09] use a neuro fuzzy network model in order to determine the condition of surge arresters. However, instead of actual thermal sensors, they applied optical, infrared sensors and used the ANN for automated digital image processing and the classification of the parts into 1 of 4 conditions. [SH10] outlined a similar ANN-based model for digital image processing. [HT13] further improved the ANN-based digital image processing for automated condition monitoring by combining a RNN with an input factor selection based on linear discriminant analysis.

Besides using ANN to determine and classify the condition of parts or machines, they can also be used to actually estimate the remaining useful lifetime (RUL) of a machine. Due to their ability to adapt to and handle incomplete data, several studies have found ANN's RUL estimations to be more accurate that classical time series analysis. [SN00], for instance, compare the prediction accuracy of various MLP to ARIMA models and show that, although the estimation based on ANN is more time-consuming, it is by far less erroneous and distorted. In order to speed up ANN-based estimation, [Hu07] presents a self-learning model based on self-organizing feature maps. Their SOM automatically identifies a subset of relevant input information and significantly reduces the time for computing. Furthermore, [MMZ09] outline an approach to model the mechanical wearout of ball bearings and directly estimate its RUL based on a dynamic RNN. ANN can also be applied in PM strategies without being used to directly evaluate conditions or estimate RULs. [Sf03] uses a RNN for the prediction of energy demand within a certain period. Based on the demand forecasts, the expected load on certain parts of an electricity generator is computed. If the expected load indicates the end of lifetime of certain parts, these are to be changed before the demand forecast window begins. In addition, ANN can be used to model and setup entire sensor infrastructures and data collection strategies. [SU03] use an RNN to find the optimal mixture and positions of sensors for the condition monitoring of the cutting tools in face milling operations.

First DSS employing ANN analyses also have already been developed. [Ya01] describe a DSS that implements a condition based maintenance strategy for a planetary gear train within an electricity generator in a power plant. The DSS determines and schedules the optimal time for maintenance activities for this particular type of gears. Similar to this, [Fu04] present an entire maintenance management framework for hydroelectric generators. They use a 4-input ANN to determine the level of degradation of certain generator parts and suggest a maintenance scheme. [Wu07] present a rather economic approach to DSS. They determine a cost-optimal time of service for ball bearings in machines without security-relevant functions. In contrast to the majority of the published studies on PM strategies, the authors do not try to avoid a run-to-failure by all means, but try to compare the expected costs of maintenance to the expected loss from machine downtimes.

4 A Roadmap to Integrated Predictive Maintenance Services

4.1 Overall research agenda

Although multiple PM applications have been described in the literature, a generally applicable approach is yet to be found. This section outlines our research roadmap and presents the tasks, which we regard to be crucial for the establishment of integrated PM services. One central aspect is to analyse, monitor and determine a machines' condition. This is usually done in a three-step procedure. At first, the life cycle of machines or single parts is determined and the drivers of their degradation processes are identified. Secondly, (sensor) data is gathered. And finally, the gathered data is processes by analytic systems in order to evaluate the current conditions.

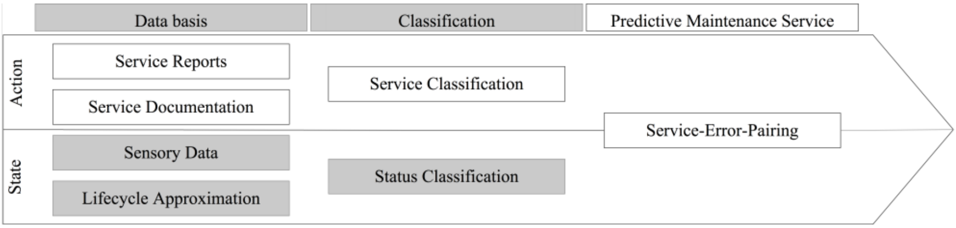

Fig. 1: The Predictive Maintenance service concept

Particularly for the latter purpose, it crucial to determine or develop standard procedures for a) data pre-processing, b) data harmonisation and c) data analysis itself. Hence, it necessary to carry out detailed and structured literature studies across a variety of scientific disciplines and develop and verify analytic artefacts for all these tasks. Regarding the data pre-processing and handling of wanted data redundancy, promising concepts and applications have been described, for instance, in the field of clinical psychology and psychiatry. [Ma14] describe a pragmatic approach to data selection by applying a combined exploratory and confirmatory factor analysis. Modern and powerful approaches to the merging and harmonization of sensor data (data fusion) are currently also addressed in maritime navigation science [SW13]. Regarding the current research on data classification with ANN, particularly studies on Convolutional Neural Networks (CNN) is broadly discussed, see, for instance [Kr12].

However, the sole information on machine conditions and possible failure is not sufficient for the development of integrated maintenance services. Once the condition of a system has been identified, it is necessary to know how to react to it. Therefore, one needs to understand the reasons for the actual classification. Usually, the number of condition classes is limited and subject to certain analytic restrictions. Consequently, a classification into a condition class can be due to a variety of errors and reasons. To identify the actual problem and the actions and maintenance services that are needed, is the second challenge to be dealt with while setting up a PM strategy. This leads to our twofold research roadmap as shown in Figure 1. To achieve an assignment between states and actions, we suggest the analysis of service reports and documentations. These documents provide valuable information about processed maintenance services, that usually begin with a distinct error and end with a solving service. The gathered information must be filtered and classified for the assignment. For this purpose, a processing by text mining algorithms or natural language processing might be an adequate approach. However, this is to be addressed in later work. As indicated by the highlights in Figure 1, our research currently focusses on the deduction of component lifecycle approximations as first important component of the predictive maintenance concept.

4.2 Our current work and state of research

During our previous research on supporting service processes in machine building companies with mobile devices, we found the density of built-in sensors and the availability of data closely depends on the complexity and actual price of a machine. The implemented sensor types and technologies are mainly determined by the individual architecture of a machine. Although a variety of sensors is integrated into a machine, not all of them can actually be used in the machines condition monitoring. Until today, whole research branches have evolved, analysing the applicability of certain sensor types for material condition diagnostics. Tribology and vibration analysis, for instance, focusses on algorithms and procedures to analyse acoustic sensors. Thereby it is possible to detect irregularities in the operations of bearings or engine cylinders. On the other hand, in order to detect leaks in hidden fuel tanks, optical sensors and algorithms and procedures from thermography or radiography can be used. A short list of different types of sensors, which have been mentioned in the literature on PM is provided in table 2.

Sensor type	Information on	Analysed in
Acoustic	Vibration, kinetic friction	[ALU93], [RB85], [Ge05], [GG06], [Ca12]
Electrical	Electrical current, electrical potential	[YL99], [HB11]
Thermal	Temperature	[Ma97]
Optical	Temperature, material density (radiography)	[La09], [Sm11], [HT13]
Force	Torque, cutting force	[Sw01], [SU01], [HB11]

Tab. 2: Overview of sensor types and their occurrences in literature

In an ongoing research project with a German machine building company, we currently support the development and introduction of a platform for service process digitalization. One objective of this platform is not only to enable online machine condition diagnostics, but also trigger those maintenance services, which are actually needed. All machines to be monitored and managed consist of more than 1000 parts and components which are subject to deterioration. Consequently, an enormous number of sensors is integrated and provides a huge and – with respect to online condition monitoring – mostly unstructured dataset, which requires extensive pre-processing and harmonisation.

In this setting, the implantation of an ANN-based diagnostic mechanism seems particularly promising and reasonable. Currently we develop the architecture for a RNN which is able to handle the complex mass sensor data in order to detect patterns and ultimately determine machine condition types. For this purpose, process and sensor data is already gathered by experts, in order to create an adequate dataset for the ANN's training. Once it is possible to detect the current condition of all monitored machines, the next step is to connect the current status to all currently necessary maintenance services. For determining which services have been carried out under which condition of a machine, historical reports from service technicians will be evaluated. By this connection, it is possible to develop and establish a fully integrated and automated predictive maintenance service management.

Two of the biggest challenges in the implementation currently are 1) determining the optimal positioning and density of sensors and 2) defining the allowed complexity of machine states. These factors determine the quality and granularity of the realizable PM strategy. If it is only possible to detect the imminence of a machine's failure in general, hardly more than a rather general maintenance task can be triggered. Hence, the classification into only few machine states might be insufficient, since those are not unambiguously related to concrete service requirements. Consequently, the insight from additional sensors and increased analytic complexity need to be carefully weight up against increased computing times and actual production costs. The life cycle analysis of the components furthermore indicates the short-term need for spare parts. Hence, another major challenge for a PM system is, not only to recognize the need for maintenance before a problem occurs, but also to recognize and trigger the resulting maintenance needs in time. Since some types of ANN are able to carry out diagnoses close to real-time, this requirement further confirms the impression of ANN being an adequate instrument. Finally yet importantly, the legal perspective needs to be addressed. The precise and complete analysis and monitoring of a machine requires full access to all relevant sensor information. This might cause resistance at machine owners, since an unbounded and steady extraction of production data may be a risk to their core business. An improvement in data security may be approached in multiple ways. On the one hand, IT-security-concepts can be extended to protect the transferred data. On the other hand, a neural network could run as a local application at the machine owner's site. However, this approach decreases the advantages of neural networks learning from failures of all machines, regardless of their operating site. Instead, only data from a single machine could provide sensor patterns that probably lack of evidence.

5 Conclusion and Outlook

The development and implementation of PM concepts and strategies is a promising approach to improve machine reliability, to avoid downtimes and to enable the optimization of maintenance processes and services. Yet, due to the steadily increasing amount and variety of built-in sensors and the resulting mass data, most companies still face a problem of information overload. Although a multitude of data processing concepts already has been applied to condition monitoring and failure forecasting, a standard practice has yet to be found. In this context, particularly ANN have gained importance in recent years. However, the available types of ANN have not been fully evaluated regarding their applicability to machine condition analysis.

The most challenging aspect in the setup of a PM-strategy is the lack of data and information standards in machine condition monitoring. Obviously, there is no such thing as a standard machine, which only consist of standard parts. However, the characteristics and behaviour of standard materials being used to build machine parts already have been studied. Hence, it might be possible to identify a combination of sensors to monitor the deterioration of single parts. Also there is no standard data structure for the collection of historical training data, yet. Another shortcoming we see in the current development of condition monitoring and PM concepts is the strong focus on the processing of sensor data. Although quite powerful text mining algorithms are available, error messages and failure and even service reports, created by service technicians or machine owners, still are mostly ignored in industrial PM applications. Although these reports have not yet been standardized either, we suspect major insights and valuable information to be hidden in this data. Hence, we strongly recommend the development of concepts for the harmonization of sensor data and data created by experts.

Finally, advanced analytic mechanisms for diagnostics are just one puzzle piece in a PM strategy. Once failures or critical conditions have been diagnosed, it becomes necessary a) to detect the actual root cause of the problem that is about to occur, b) to identify the adequate maintenance service for this problem, c) to schedule the service and d) to monitor and analyse the post service system conditions. Consequently, if an appropriate analytic system has been developed, the required research has just begun.

References

[ALU93] Alguindigue, I. E.; Loskiewicz-Buczak, A. and Uhrig, R. E. 1993. “Monitoring and diagnosis of rolling element bearings using artificial neural networks”, IEEE Transactions on Industrial Electronics (40:2), pp. 209–217.

[Al09] Almeida, C. A. L.; Braga, A. P.; Nascimento, S.; Paiva, V.; Martins, H. J. A.; Torres, R. and Caminhas, W. M. 2009. “Intelligent Thermographic Diagnostic Applied to Surge Arresters: A New Approach”, IEEE Transactions on Power Delivery (24:2), pp. 751–757.

[Br12] Brezak, D.; Bacek, T.; Majetic, D.; Kasac, J. and Novakovic, B. 2012. “A comparison of feed-forward and recurrent neural networks in time series forecasting”, IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr), pp. 1–6.

[Ca05] Carnero, M. C. 2005. “Selection of diagnostic techniques and instrumentation in a predictive maintenance program. A case study”, Decision Support Systems (38:4), pp. 539–555.

[CG87] Carpenter, G. A. and Grossberg, S. 1987. “A massively parallel architecture for a self-organizing neural pattern recognition machine”, Computer Vision, Graphics, and Image Processing (37:1), pp. 54–115.

[Ca12] Cartella, F.; Liu, T.; Meganck, S.; Lemeire, J. and Sahli, H. 2012. “Online adaptive learning of Left-Right Continuous HMM for bearings condition assessment”, Journal of Physics: Conference Series (364), p. 12031.

[Fu04] Fu, C.; Ye, L.; Liu, Y.; Yu, R.; Iung, B.; Cheng, Y. and Zeng, Y. 2004. “Predictive Maintenance in Intelligent-Control-Maintenance-Management System for Hydroelectric Generating Unit”, IEEE Transactions on Energy Conversion (19:1), pp. 179–186.

[FAU15] Furtak, S.; Avital, M. and Ulslev Pedersen, R. 2015. “Sensing the Future: Designing Predictive Analytics with Sensor Technologies”, in 23rd European Conference on Information Systems (ECIS) 2015.

[GG06] Gebraeel, N. and Gebraeel, N. 2006. “Sensory-Updated Residual Life Distributions for Components with Exponential Degradation Patterns”, IEEE Transactions on Automation Science and Engineering (3:4), pp. 382–393.

[Ge05] Gebraeel, N. Z.; Lawley, M. A., Li, R. and Ryan, J. K. 2005. “Residual-life distributions from component degradation signals: A Bayesian approach”, IIE Transactions (37:6), pp. 543–557.

[Gr76] Grossberg, S. 1976. “Adaptive pattern classification and universal recoding: I. Parallel development and coding of neural feature detectors”, Biological Cybernetics (23:3), pp. 121–134.

[HB11] Hashemian, H. M. and Bean, W. C. 2011. “State-of-the-Art Predictive Maintenance Techniques”, IEEE Transactions on Instrumentation and Measurement (60:10), pp. 3480–3492.

[He04] Hevner, A. R.; March, S. T.; Park, J. and Ram, S. 2004. “Design science in information systems research”, MIS quarterly (28:1), pp. 75–105.

[Hu07] Huang, R.; Xi, L.; Li, X.; Richard Liu, C.; Qiu, H. and Lee, J. 2007. “Residual life predictions for ball bearings based on self-organizing map and back propagation neural network methods”, Mechanical Systems and Signal Processing (21:1), pp. 193–207.

[HT13] Huda, A. S. N. and Taib, S. 2013. “Application of infrared thermography for predictive/preventive maintenance of thermal defect in electrical equipment”, Applied Thermal Engineering (61:2), pp. 220–227.

[IV88] Ives, B. and Vitale, M. R. 1988. “After the Sale: Leveraging Maintenance with Information Technology”, MIS Quarterly (12:1), pp. 7–21.

[Ko82] Kohonen, T. 1982. “Self-organized formation of topologically correct feature maps”, Biological Cybernetics (43:1), pp. 59–69.

[Kr12] Krizhevsky, A.; Sutskever, I. and Hinton, G. E., 2012. “Imagenet classification with deep convolutional neural networks.”, Advances in neural information processing systems, pp. 1097-1105.

[La14] Lasi, H.; Fettke, P.; Kemper, H.-G.; Feld, T. and Hoffmann, M. 2014. “Industry 4.0”, Business & Information Systems Engineering (6:4), pp. 239–242.

[Ma97] Manduchi, G.; Marinetti, S.; Bison, P. and Grinzato, E. 1997. “Application of neural network computing to thermal non-destructive evaluation”, Neural Computing & Applications (6:3), pp. 148–157.

[Ma14] Marsh, H. W.; Morin, A. J. S.; Parker, P. D. and Kaur, G. 2014 “Exploratory Structural Equation Modeling: An Integration of the Best Features of Exploratory and Confirmatory Factor Analysis”, Annu. Rev. Clin. Psychol., Bd. 10, Nr. 1, pp. 85–110, March 2014.

[MP43] McCulloch, W. S. and Pitts, W. 1943. “A logical calculus of the ideas immanent in nervous activity”, Bulletin of Mathematical Biophysics (5), pp. 115–133.

[MMZ09] Medjaher, K.; Moya, J.-Y. and Zerhouni, N. 2009. “Failure prognostic by using dynamic Bayesian Networks.”, in 2nd IFAC Workshop on Dependable Control of Discrete Systems, DCDS’09. (Vol. 1), IFAC, pp. 291–296.

[Pe07] Persona, A.; Regattieri, A.; Pham, H. and Battini, D. 2007. “Remote control and maintenance outsourcing networks and its applications in supply chain management”, Journal of Operations Management (25:6), pp. 1275–1291.

[RMD02] Rauber, A.; Merkl, D. and Dittenbach, M. 2002. “The growing hierarchical self-organizing map: exploratory analysis of high-dimensional data”, IEEE Transactions on Neural Networks (13:6), pp. 1331–1341.

[RB85] Renwick, J. T. and Babson, P. E. 1985. “Vibration Analysis—A Proven Technique as a Predictive Maintenance Tool”, Industry Applications, IEEE Transactions on (2), pp. 324–332.

[Ro14] Roland Berger. 2014. “Evolution of service: Capturing value pockets in the service business”, (available at http://www.rolandberger.de/media/pdf/Roland_Berger_taC_ Evolution_of_Service_2014 0107pdf).

[Ro58] Rosenblatt, F. 1958. “The perceptron: A probabilistic model for information storage and organization in the brain.”, Psychological Review (65:6), pp. 386–408.

[RHW86] Rumelhart, D. E.; Hinton, G. E. and Williams, R. J. 1986. “Learning representations by back-propagating errors”, Nature (323:6088), pp. 533–536.

[SU03] Saglam, H. and Unuvar, A. 2003. “Tool condition monitoring in milling based on cutting forces by a neural network”, International Journal of Production Research (41:7), pp. 1519–1532.

[Sf03] Sfetsos, A. 2003. “Short-term load forecasting with a hybrid clustering algorithm”, in Generation, Transmission and Distribution, IEE Proceedings- (Vol. 150), IET, pp. 257–262.

[SH10] Shafi, M. A. and Hamzah, N. 2010. "Internal fault classification using artificial neural net-work", in Power Engineering and Optimization Conference (PEOCO), 2010 4th International, IEEE, pp. 352–357.

[SN00] Shao, Y. and Nezu, K. 2000. "Prognosis of remaining bearing life using neural networks", Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering (214:3), pp. 217–230.

[Sm11] Smet, V.; Forest, F.; Huselstein, J.-J.; Richardeau, F.; Khatir, Z.; Lefebvre, S. and Berkani, M. 2011. "Ageing and Failure Modes of IGBT Modules in High-Temperature Power Cy-cling", IEEE Transactions on Industrial Electronics (58:10), pp. 4931–4941.

[SvB12] Sonnenberg, C. and vom Brocke, J., 2012. "Evaluations in the science of the artificial–reconsidering the build-evaluate pattern in design science research", in: International Conference on Design Science Research in Information Systems. Springer, pp. 381–397.

[SW13] Stateczny, A. and Witold, K., 2013. "Sensor data fusion in inland navigation." 2013 14th Inter-national Radar Symposium (IRS). Vol. 1. IEEE, pp. 264-269.

[Sw01] Swanson, D. C. 2001. "A general prognostic tracking algorithm for predictive maintenance", (Vol. 6), IEEE, pp. 2971–2977.

[Wa02] Wang, H. 2002. "A survey of maintenance policies of deteriorating systems", European journal of operational research (139:3), pp. 469–489.

[Wu07] Wu, S.; Gebraeel, N.; Lawley, M. A. and Yih, Y. 2007. "A Neural Network Integrated Decision Support System for Condition-Based Optimal Predictive Maintenance Policy", IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans (37:2), pp. 226–236.

[Ya01] Yam, R. C. M.; Tse, P. W.; Li, L. and Tu, P. 2001. "Intelligent Predictive Decision Support System for Condition-Based Maintenance", The International Journal of Advanced Manufacturing Technology (17:5), pp. 383–391.

[YL99] Yang, S. K. and Liu, T. S. 1999. "State estimation for predictive maintenance using Kalman filter", Reliability Engineering & System Safety (66:1), pp. 29–39.

[Zo07] Zou, H. F.; Xia, G. P.; Yang, F. T. and Wang, H. Y. 2007. "An investigation and comparison of artificial neural network and time series models for Chinese food grain price forecasting", Neurocomputing (70:16–18), pp. 2913–2923.